Deep learning for Cosmology

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- Fast and furious General Relativity

~ 36% of open problems in physics involve gravity

(see www.wikipedia.org/wiki/List_of_unsolved_problems_in_physics)

gravity

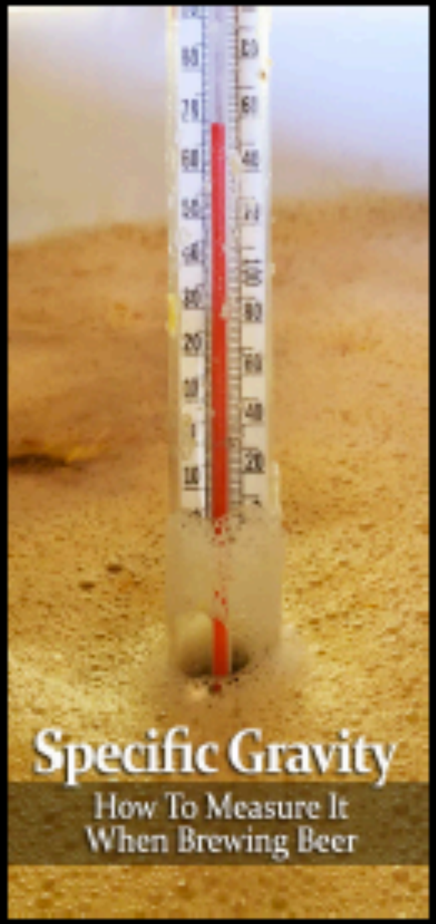
'gravɪti/

noun

1. [Physics]
   the force that attracts a body towards the centre of the earth, or towards any other physical body having mass.

2. extreme importance; seriousness.

3. in the context of fermenting alcoholic beverages, refers to the specific gravity, or relative density compared to water, of the wort or must at various stages in the fermentation.



$$\boxed{\frac{d}{dt}\text{gravity} \propto \text{alcohol } \%}$$

$\Rightarrow \exists$ at least a useful "test" of gravity!

Metric: way to describe distance/time

$$ds^2 = c^2 dt^2 - g_{ij} dx^i dx^j$$

$$ds^2 = c^2 dt^2 - S^2(t) h_{ij} dx^i dx^j$$

$$ds^2 = c^2 dt^2 - a^2(t) \left[\frac{dr^2}{1 - kr^2} + r^2 (d\theta^2 + \sin^2\theta d\phi^2) \right]$$

Friedmann–Lemaître–Robertson–Walker (FLRW)

Specify way in which curvature determine/ response to matter

Cosmological Constant

$$\Lambda g_{\mu\nu} + G_{\mu\nu} = 8\pi G_0 T_{\mu\nu}$$

Curvature

Newton's constant

Matter

$$G_{\mu\nu} \sim g, \partial g, \partial^2 g \qquad T_{\mu\nu} \sim \rho, P$$

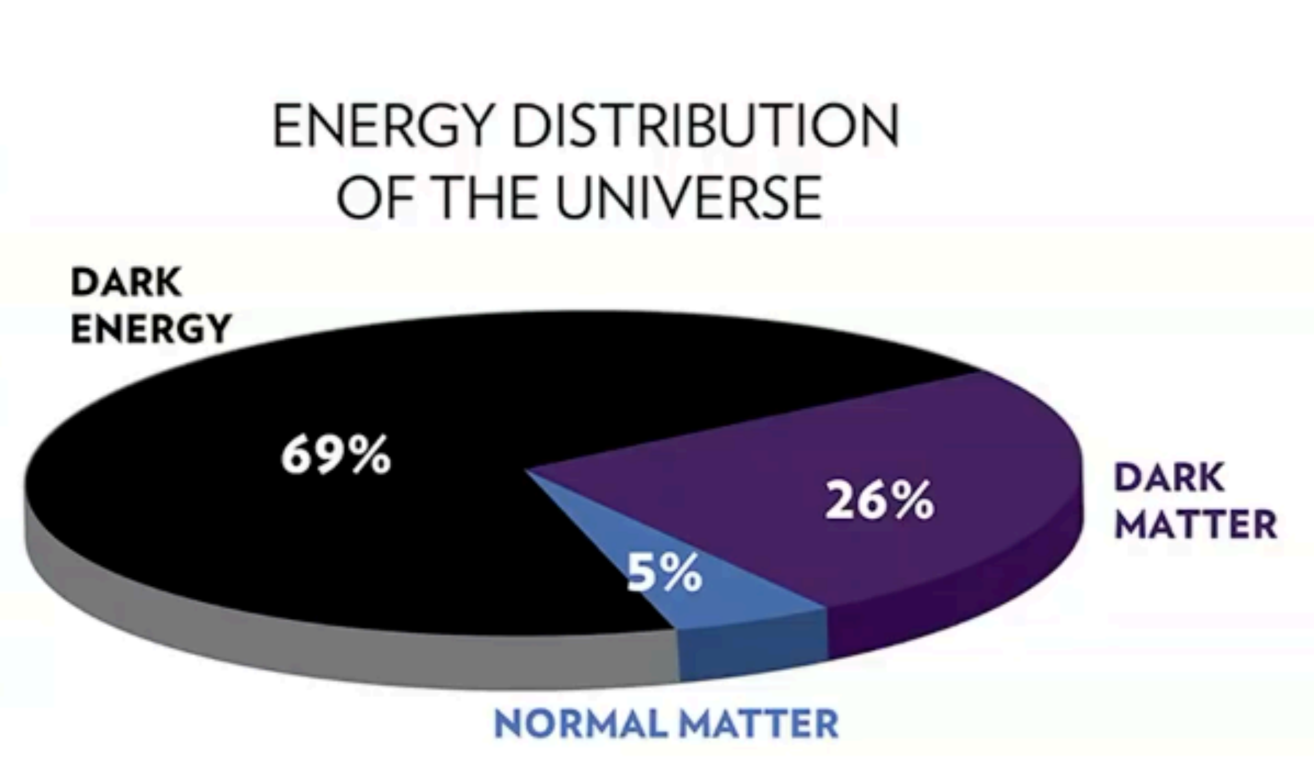
Gravity model
(GR+FLRW)

+

Data
(CMB, Supernovae, BAO,...)

=

Inconsistency ⟶ Dark matter + Dark energy



Initial Conditions

Inflation

Modified gravity (high curvature)?

Structure formation

Dark Matter

Modified Newtonian Dynamics?

Acceleration

Λ

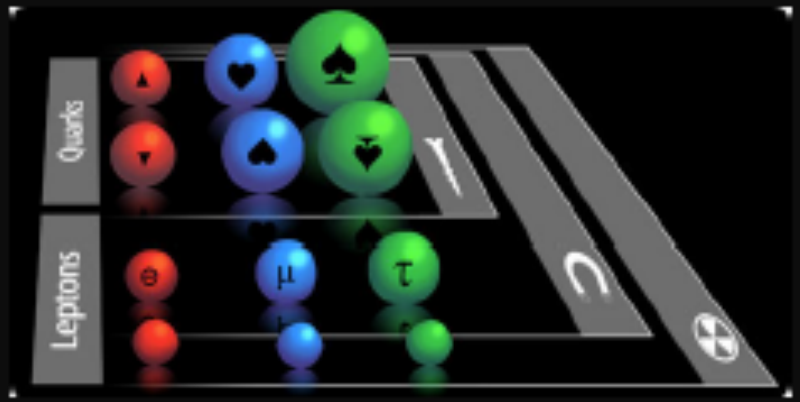
Modified gravity (low curvature)?

Metric Symmetries

$$-dt^2 + a(t)^2 d\vec{x}^2$$

Homogeneous & isotropic

Standard Matter



Theory of Gravity

$$G_{\mu\nu}[g_{\mu\nu}] = 8\pi G T_{\mu\nu}$$

Einstein's GR

Simplest model of dark energy

Cosmological constant Λ

$$w_{DE} = -1$$

This corresponds to the energy scale

$$\rho_\Lambda = \frac{3H_0^2}{8\pi G} \approx 10^{-47}\mathrm{Gev}^4$$

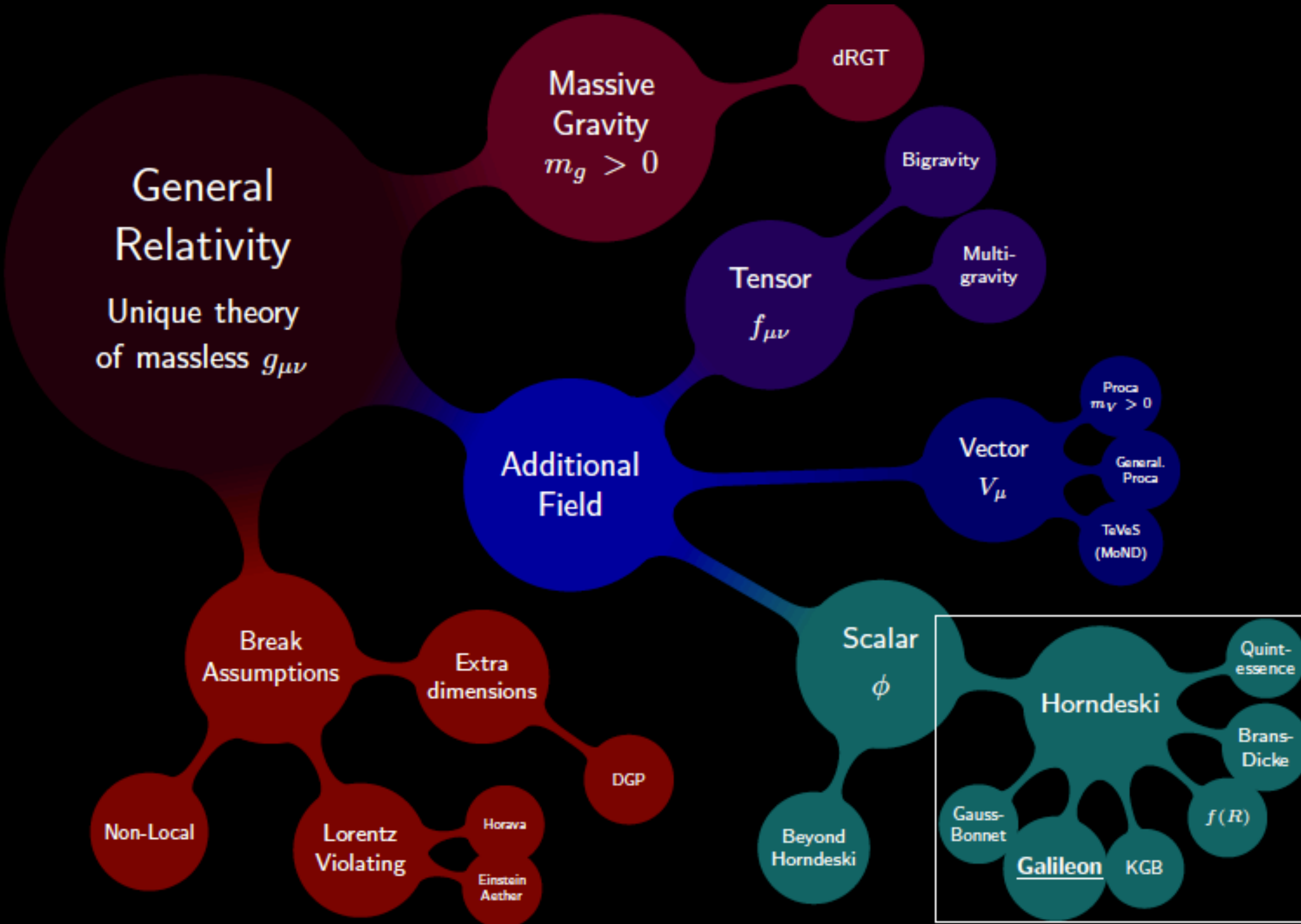
If this originates from vacuum energy in particle physics

$$\rho_{vac} \approx m_{pl}^4 \approx 10^{74}\mathrm{Gev}^4$$

Huge difference compared to the present value…

Cosmological constant problem

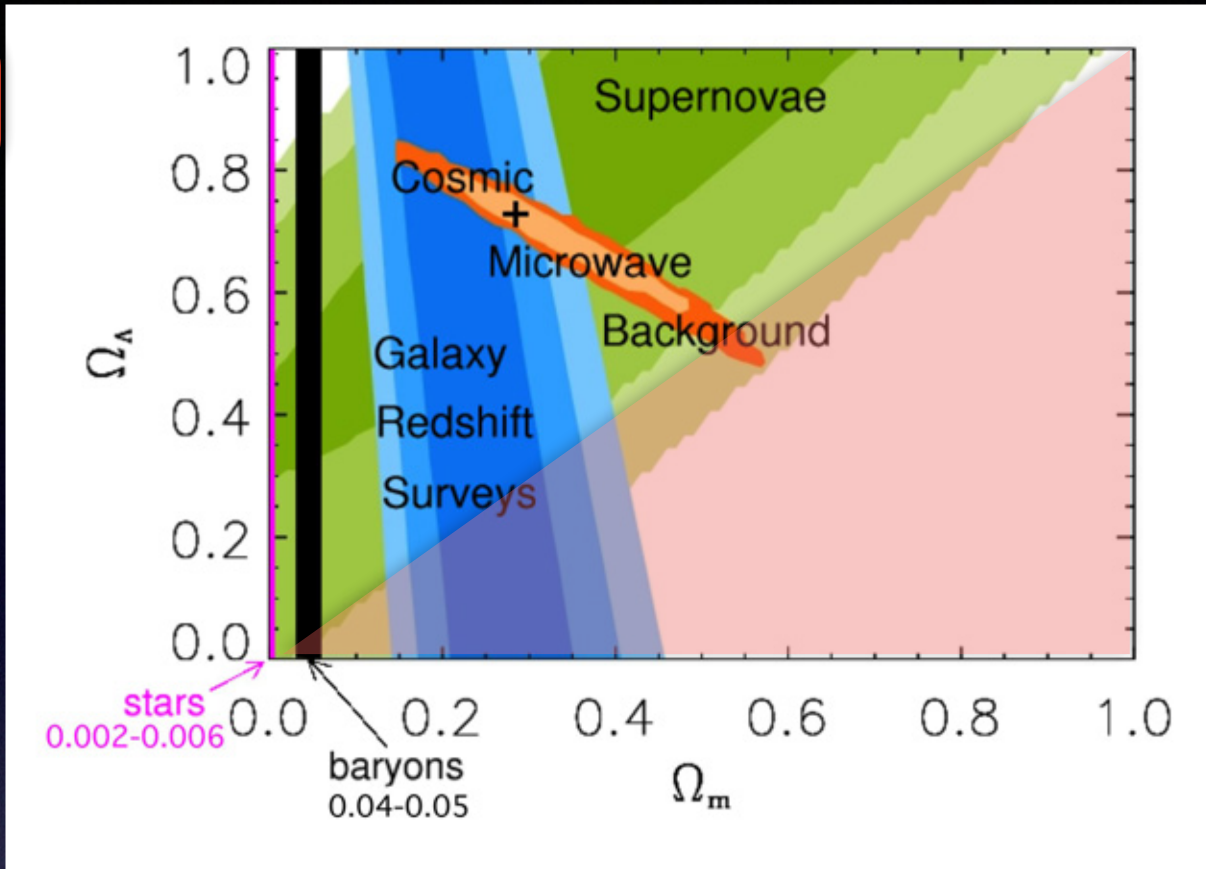
10^{121} times larger than the observed value


General Relativity
Unique theory of massless $g_{\mu\nu}$
Massive Gravity
$m_g > 0$
dRGT
Bigravity
Multi-gravity
Tensor
$f_{\mu\nu}$
Additional Field
Vector
V_μ
Proca
$m_V > 0$
General. Proca
TeVeS (MoND)
Scalar
ϕ
Horndeski
Quint-essence
Brans-Dicke
$f(R)$
Gauss-Bonnet
Galileon
KGB
Beyond Horndeski
Break Assumptions
Extra dimensions
DGP
Non-Local
Lorentz Violating
Horava
Einstein Aether

- Precision Cosmology State-of-Art

[Adapted from Verde et al 2011]

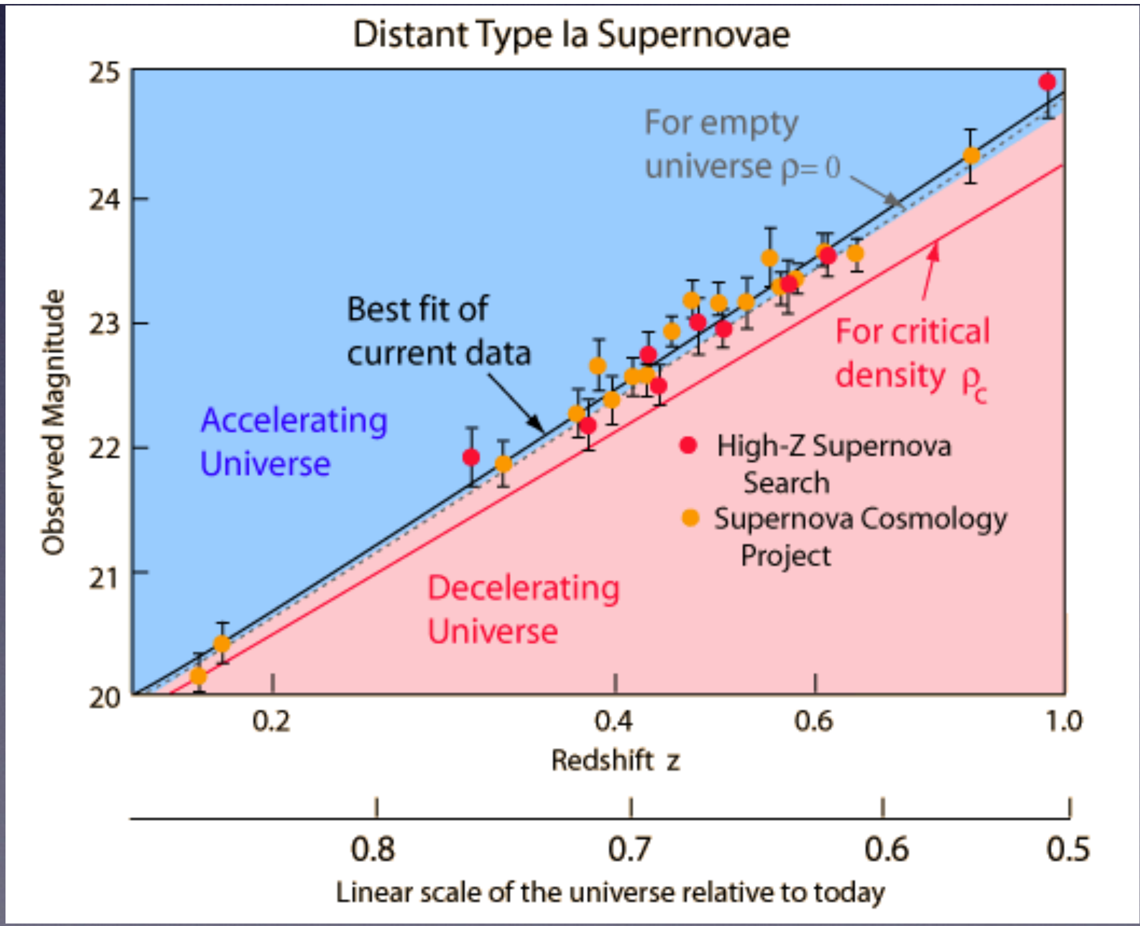
How do we proof dark energy?



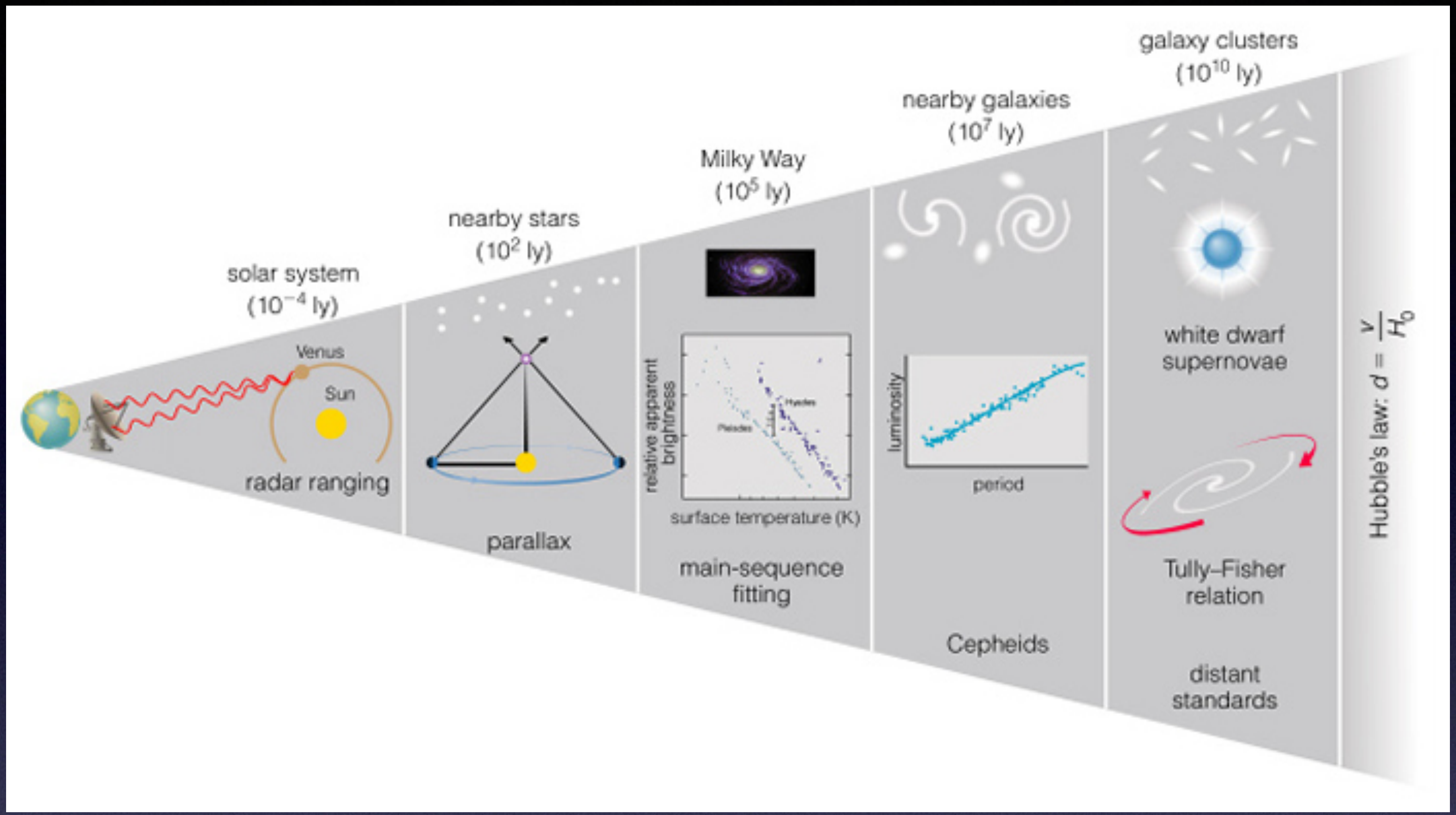
Our universe is expanding. And that expansion appears to be accelerating.

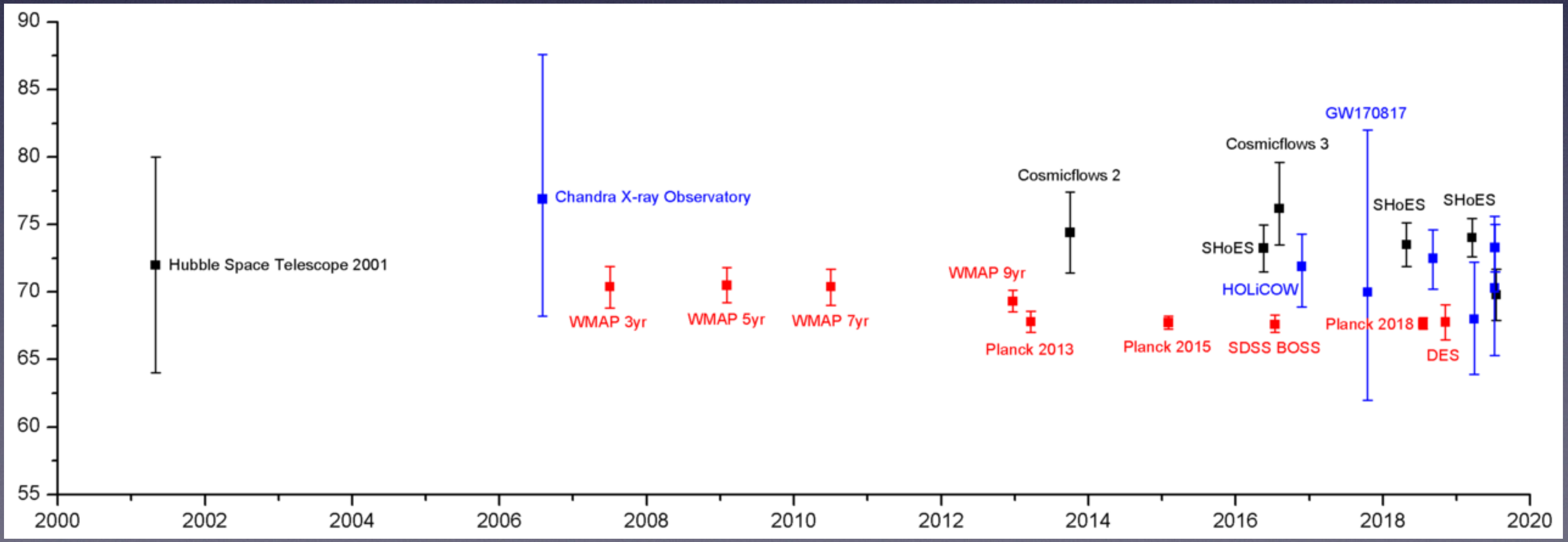
But gravity pulls masses together. It does not push them apart!

What is causing the acceleration?



Cosmic distance ladder





- Astrophysical Surveys

Cosmology meets Big Data

The challenges for modern surveys

Square Kilometre Array (SKA) project (South Africa + Australia) (2016)

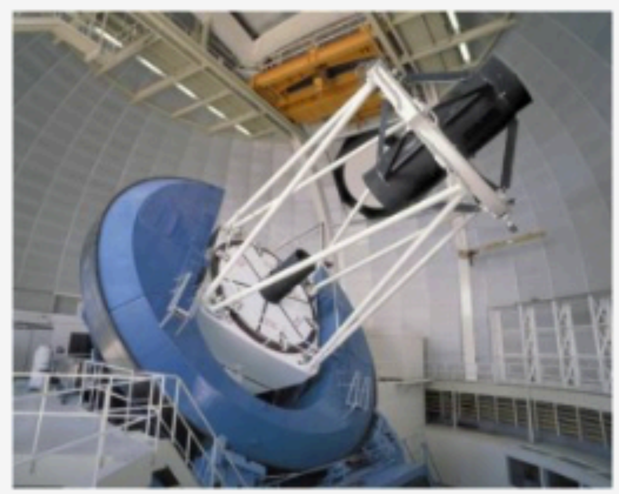
Combine the signals received from thousands of small antennas spread over a distance of more than 3000 km. When operational, as much as **700TB/ second of data** will flow from the Square Kilometre Array

The challenges for modern surveys

Dark Energy Spectroscopic Instrument (DESI) (USA) (2018)

Will measure the effect of dark energy on the expansion of the universe. It will obtain optical spectra for **tens of millions of galaxies and quasars**, constructing a 3-dimensional map spanning the nearby universe to 10 billion light years.

Exterior of Kitt Peak Mayall 4-meter telescope (Image: NOAO/AURA/NSF)



The Kitt Peak National Observatory's Mayall 4-meter telescope (Image: NOAO/AURA/NSF)

A model of the Mayall telescope with a DESI Prime Focus Assembly

The challenges for modern surveys

$\Longrightarrow$ Modern surveys will provide large volumes of high quality data

A Blessing

- Unprecedented statistical power
- Great potential for new discoveries

A Curse

- Existing methods are reaching their limits (computational cost, accuracy) at every step of the science analysis
- Control of systematic uncertainties becomes paramount

$\Longrightarrow$ Dire need for **novel data analysis techniques** to fully realize the potential of modern surveys.

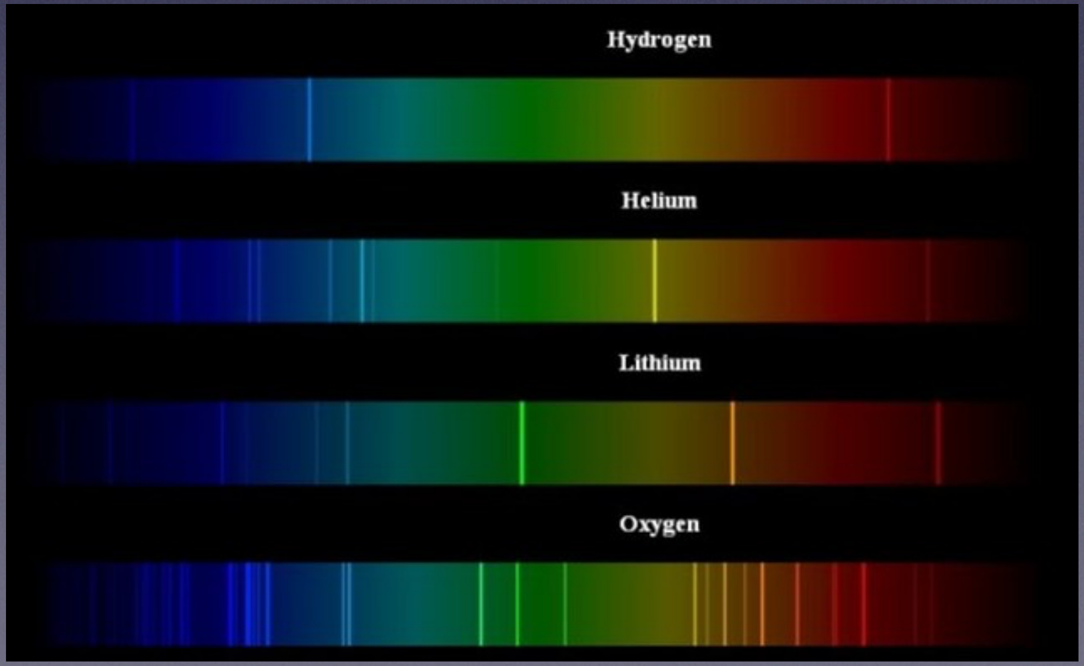
What do the data look like?

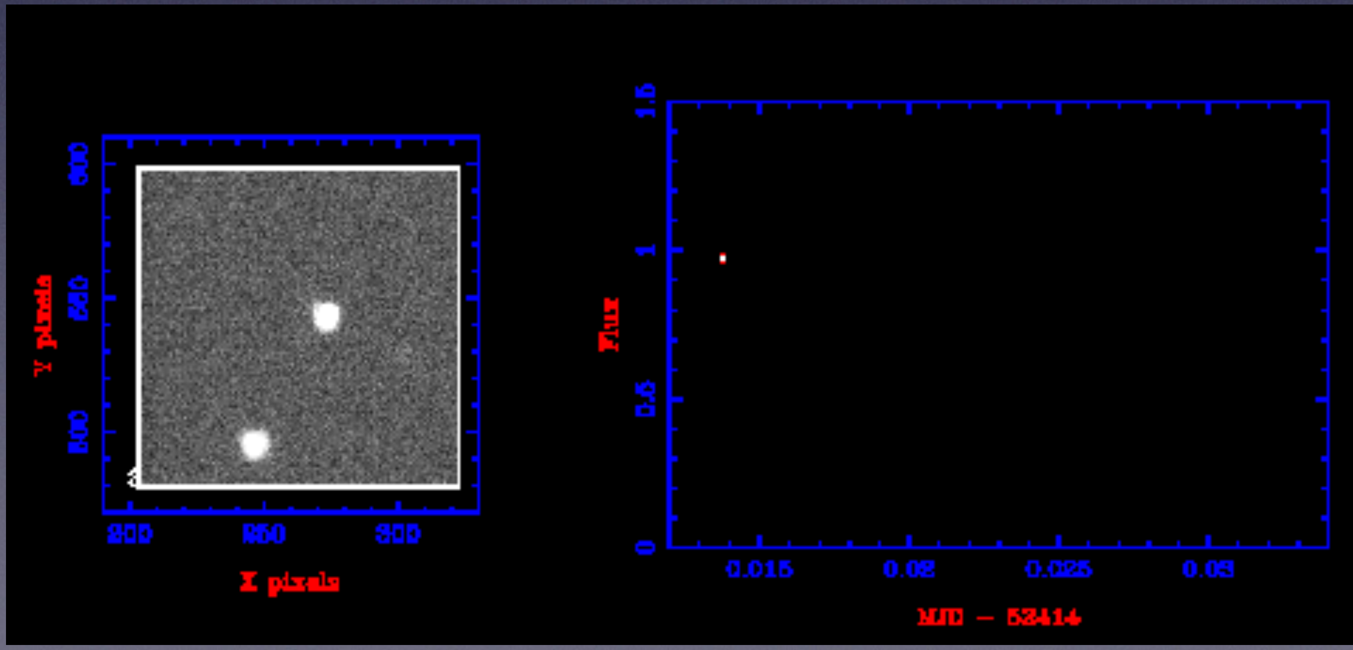
Surveys usually make either

spectroscopic observations **or** **photometric observations**

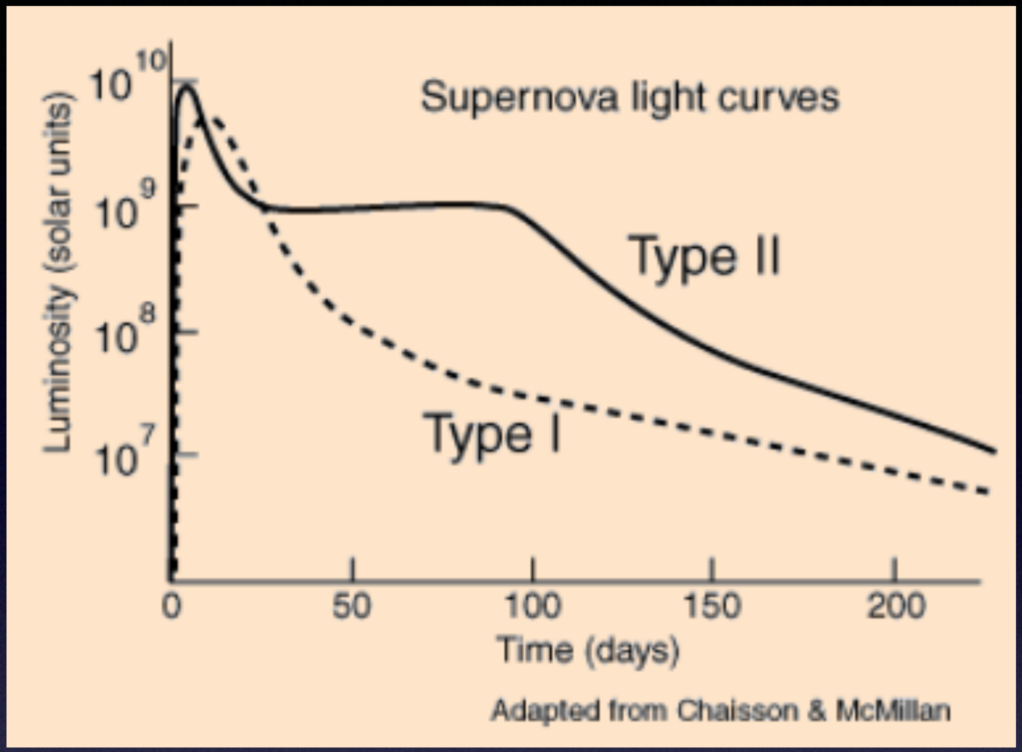
- Measures the photon count at thousands of wavelengths.
- Spectrum allows for identifying chemical components of the observed object.

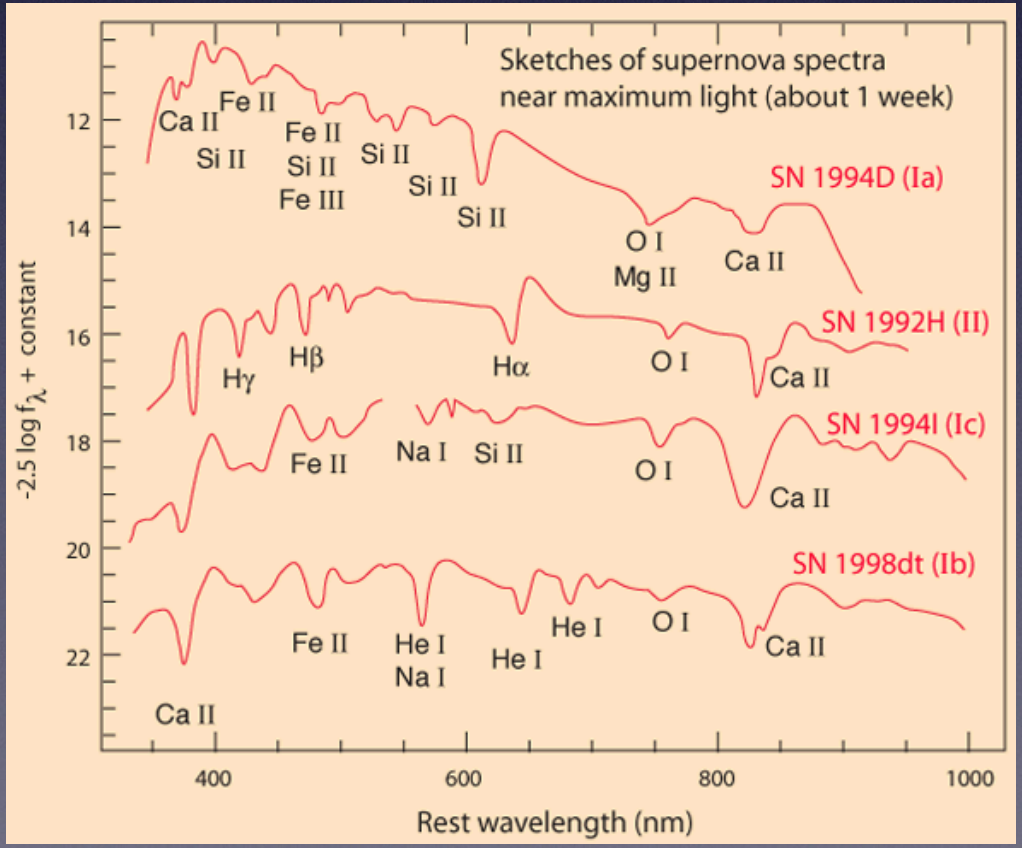
- Takes images using a CCD.
- Typically acquired through only a handful of broad-band filters.





What about Supernovae?



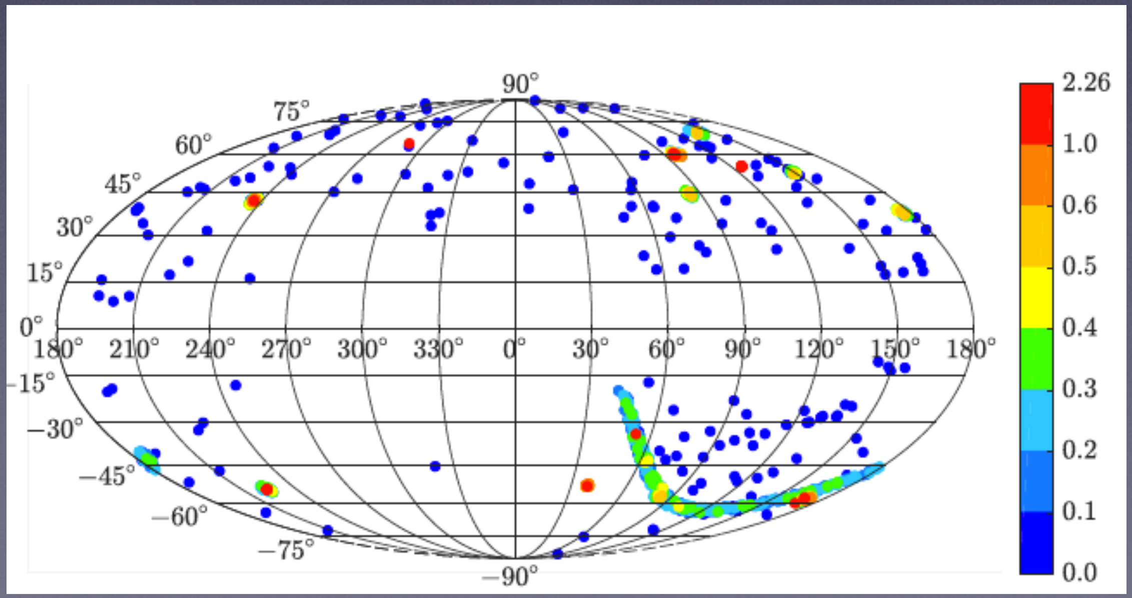


Nobel Prize in Physics 2011

"for the discovery of the accelerating expansion of the Universe through observations of distant supernovae."

Observation SNeIa: Pantheon 2018

1048 events in $0.01 < z < 2.26$



More observations…

- BAO data: acoustic density waves in the primordial plasma of the early universe. [L. Anderson et al. BOSS Collaboration. Mon.Not.Roy.Astron.Soc. 441, 24 (2014)]

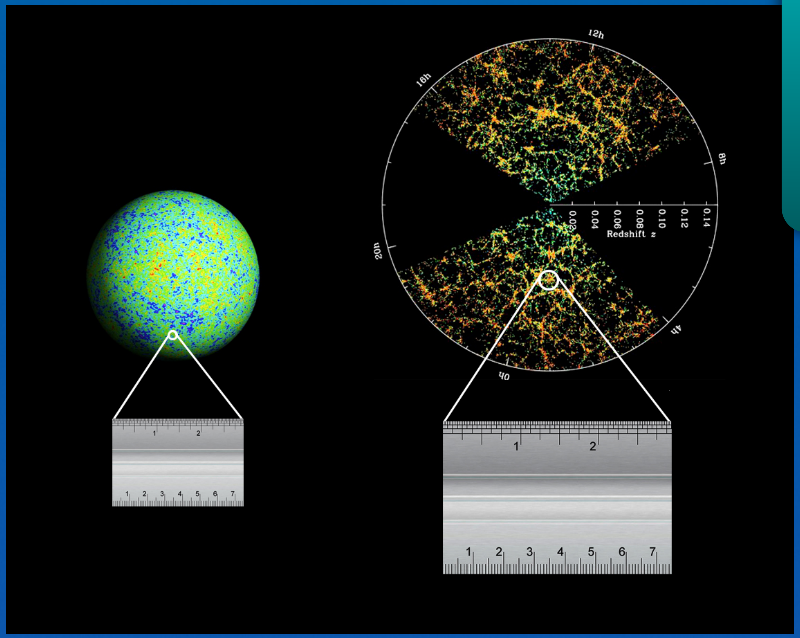
- Cosmic Chronometers (C-C) data: This kind of sample gives a measurement of the expansion rate without relying on the nature of the metric between the chronometer and us. A full compilation of the latter include 38 measurements of H(z) in the range $0.07 < z < 2.3$. [F. Anagnostopoulos, et-al (2017)]

- Redshift space distortions data: they provide a mechanism to measure the build-up of structure: $f\sigma_8(z)$. [Kimura et al (2017)]

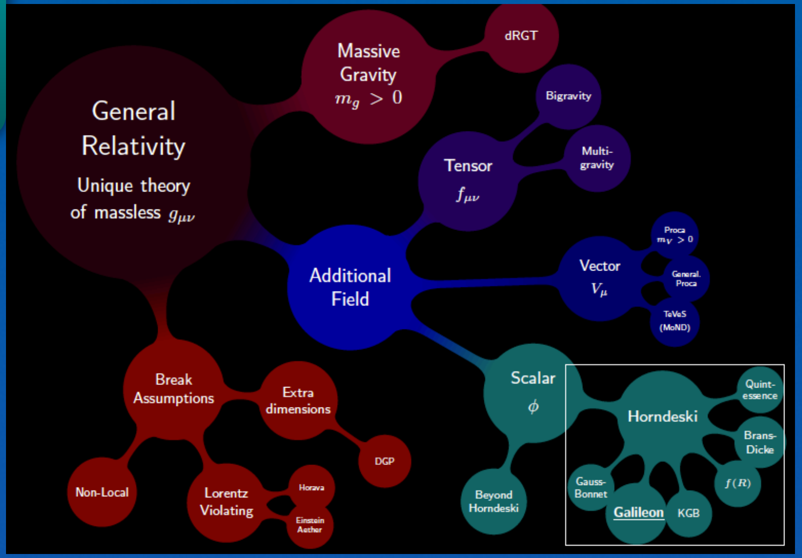
- Gravitational-wave standard sirens: present a novel approach for the determination of the Hubble constant. [Zhang, X. Sci. China-Phys. Mech. Astron (2019)]

- Dark Energy Cosmostatistics

Data
(CMB, structure formation,
BAO,…)



Models
Models parameters
LCDM?
w?
.



Inverse problem

Most cosmological models are inverse problems, where we have a dataset and want to infer something.

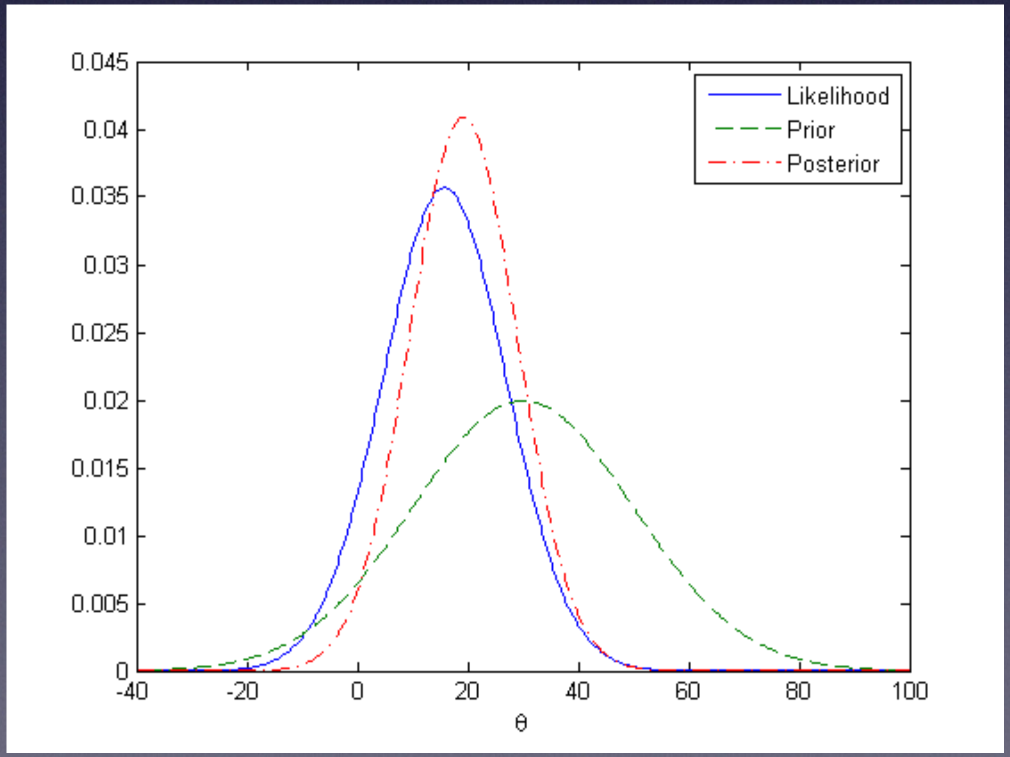
Tasks:
(1) Hypothesis testing
(2) Parameter inference
(3) Model selection

What is bayesian analysis?

General method for updating the probability estimate for a theory as additional data are acquired.

Likelihood → $P(x|\theta)$; Prior → $P(\theta)$ (Challenge 2!)

$$\text{Posterior} \longleftarrow P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)} \longrightarrow \text{Evidence}$$



The inputs of a Bayesian analysis are of two sorts:

The prior: it includes modelling assumptions, both theoretical and experimental.

The data: in cosmology, these can be the temperature of CMB map, galaxy redshifts, etc.

Bayesian model selection

Cosmological model

Astrophysical data

Prior information (free parameters)

Bayes theorem: update the prior model probability to the posterior model probability → $\mathcal{E} = \int \mathcal{L}(\theta) P(\theta) d\theta.$

Solution: Multi-nested sampling

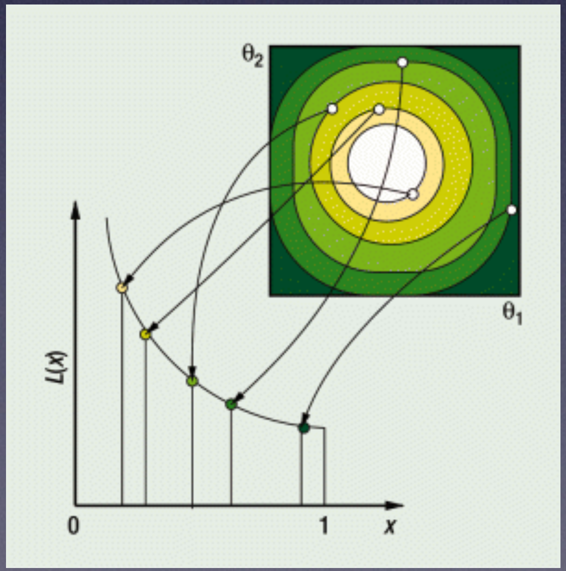
[A.R.Liddle et al Phys.Rev.D 74, 123506 (2006)]

Bayes factor: $\mathcal{B}_{ij} = \mathcal{E}_i / \mathcal{E}_j$

where reference model $(\mathcal{E}_i)$ highest evidence is ΛCDM

Jeffreys's scale:

$\ln B_{i0}$	Strength of evidence
> 5	Strong evidence for model i
$[2.5, 5]$	Moderate evidence for model i
$[1, 2.5]$	Weak evidence for model i
$[-1, 1]$	Inconclusive
$[-2.5, -1]$	Weak evidence for ΛCDM
$[-5, -2.5]$	Moderate evidence for ΛCDM
< -5	Strong evidence for ΛCDM



On the road to solutions…

Tension

H_0 from local sources (Cefeids, SNeIa)

H_0 from the sound horizon observed from CMB

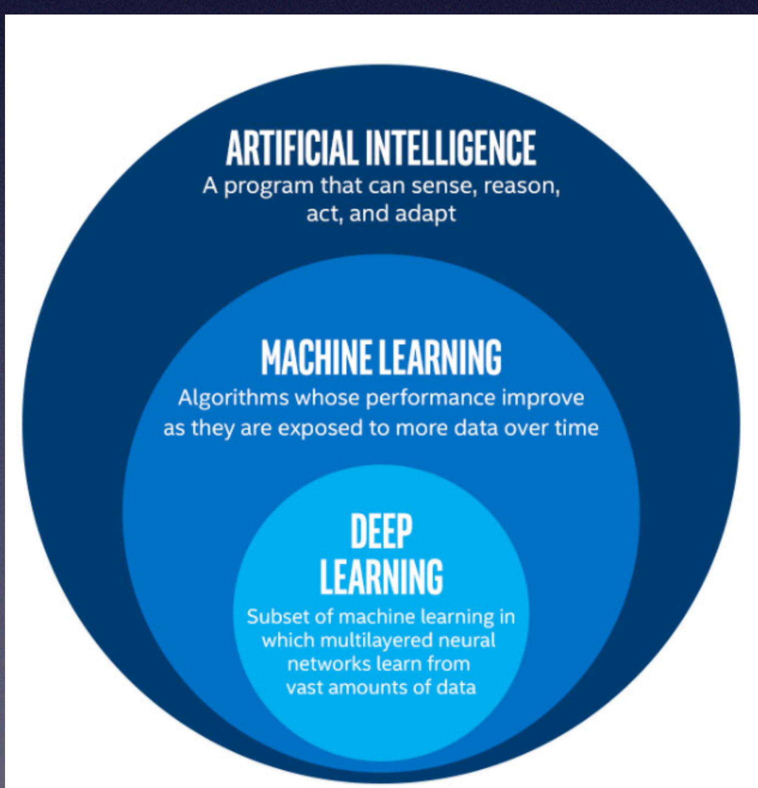
Possible solutions

- Evidence for a non-constant dynamical dark energy
- Beyond the LCDM standard model
- Model-independent approach
- Independent samples

- Deep Learning at scale for cosmology research

Deep Learning at scale for cosmology research

- An example of Deep Learning allowing us to handle the volume and data rate of future surveys



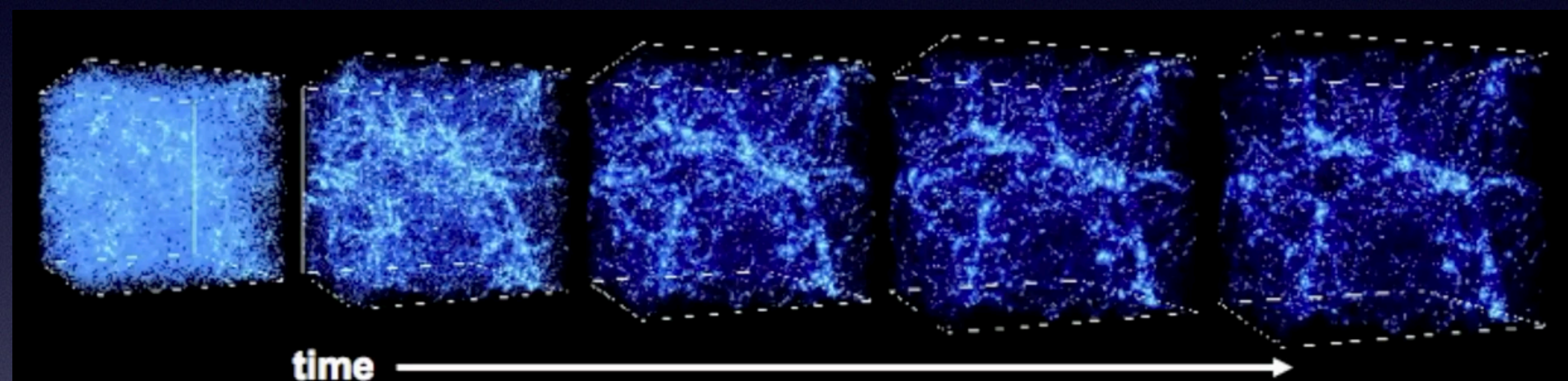
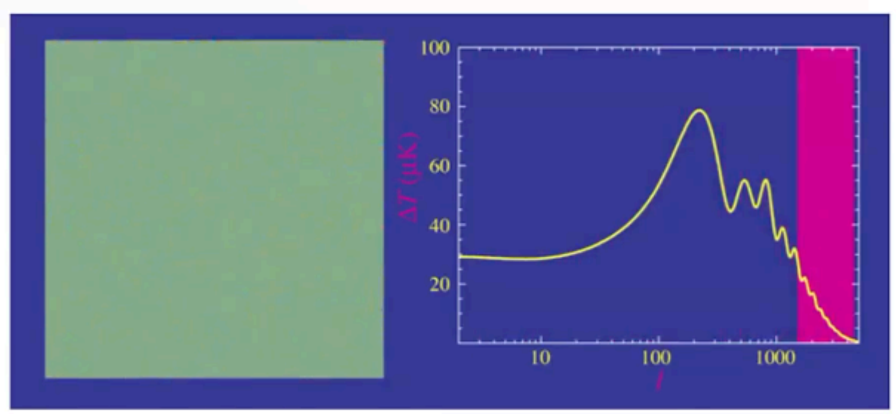


Image courtesy of Andrey Kravtsov and Anatoly Klypin



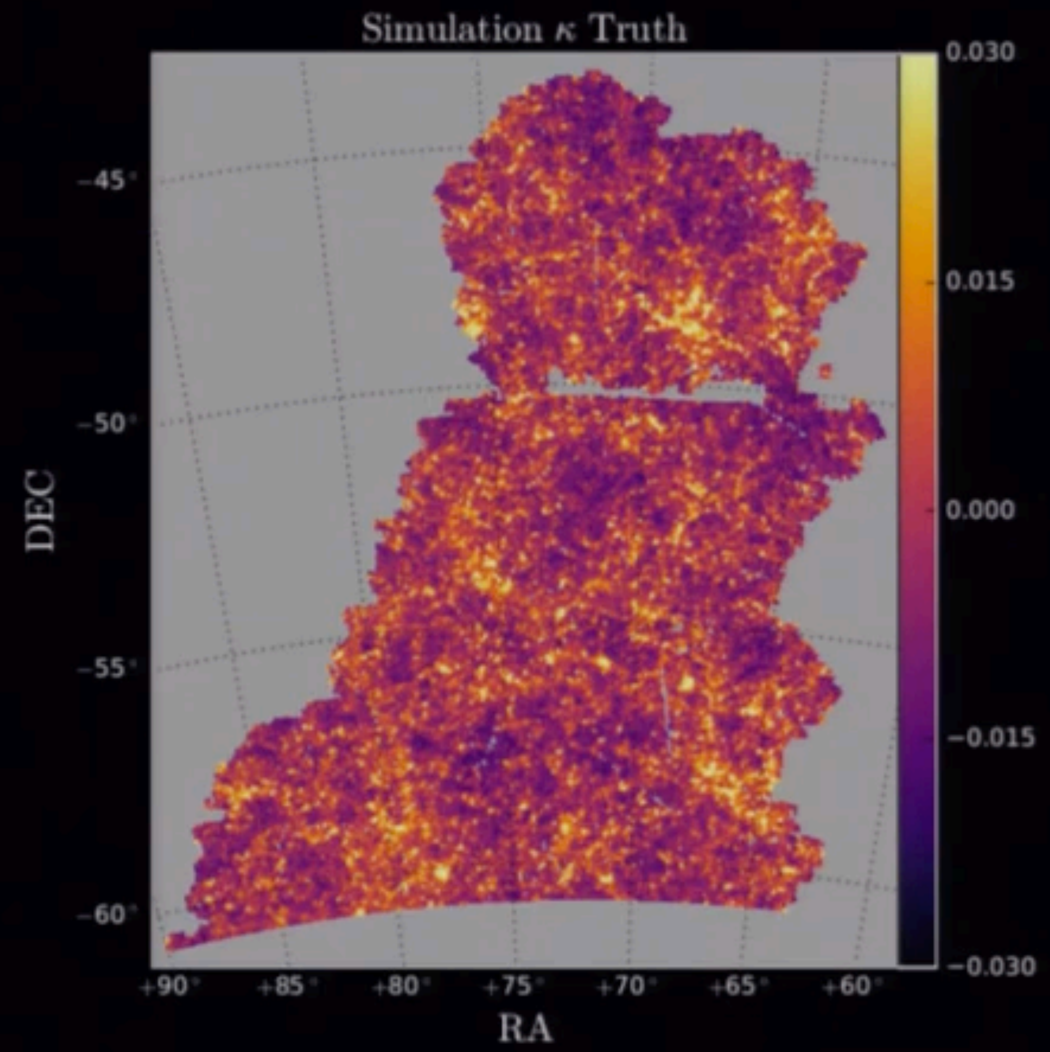
Wayne Hu and Martin White, Scientific American 290N2 44 (2004)

Experimenting with the universe:

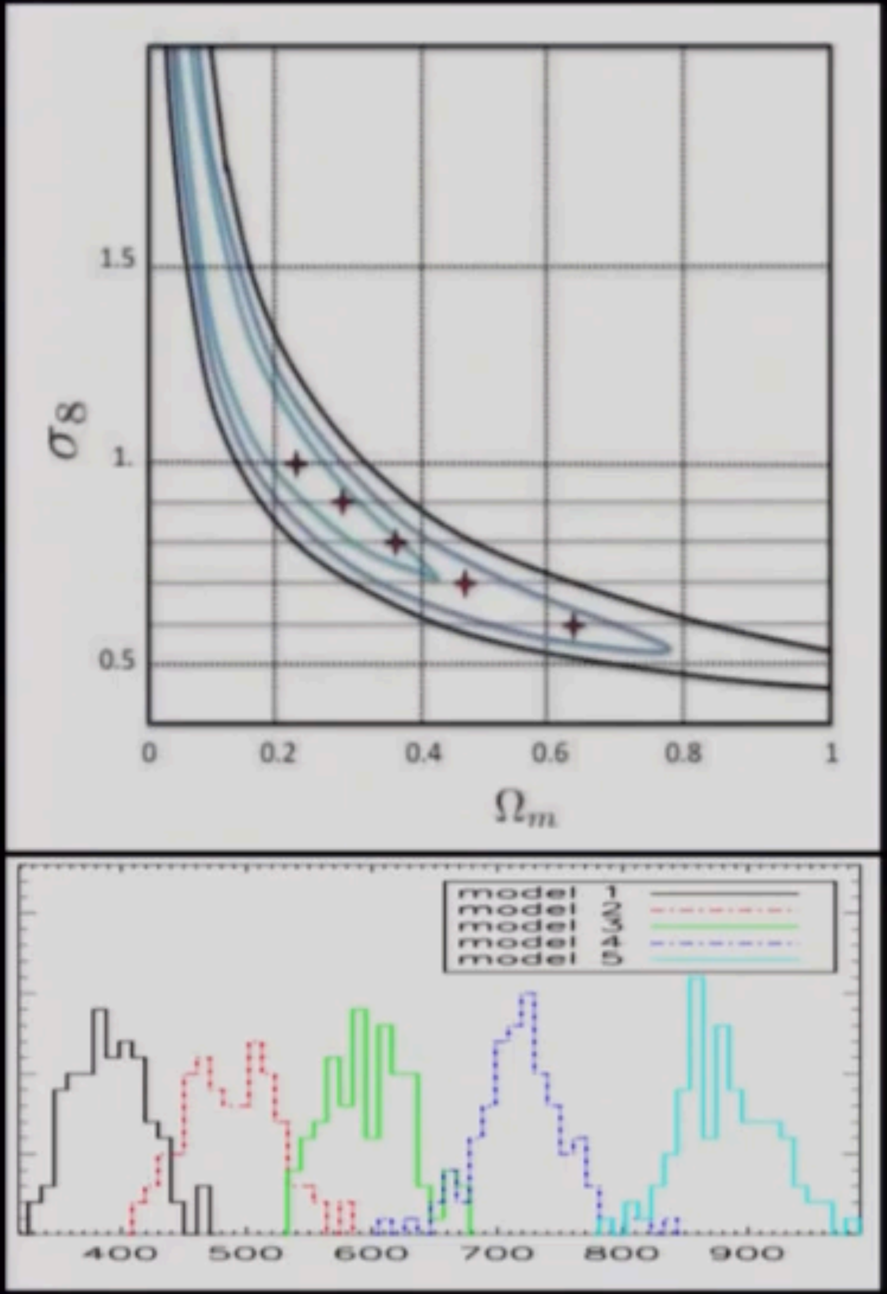
Compare simulations to observation
Often use reduced statistics like the power spectrum

#io18

A motivating example



Reconstructed convergence map on simulated DES-SV



Pires et al. (2009)

Can I ask a Deep Neural Network to infer (σ_8, Ω_m) from raw convergence maps?

let us rephrase the question

- I assume a forward graphical model of the observations:

$$p(x) = p(x|\theta)\ p(\theta)$$

All I ask is the ability to sample from the model, to obtain $\mathcal{D} = \{x_i, \theta_i\}_{i \in \mathbb{N}}$

- I am going to assume $q_\phi(\theta|x)$ a **parametric conditional density**
- Optimize the parameters ϕ of q_ϕ according to

$$\min_{\phi} \sum_{i} -\log q_\phi(\theta_i|x_i)$$

In the limit of **infinite samples** and **sufficient flexibility**

$$\boxed{q_{\phi^*}(\theta|x) \approx p(\theta|x)}$$

$\Longrightarrow$ One can asymptomatically recover the posterior by optimizing a parametric estimator over the Bayesian joint distribution

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- I assume a forward graphical model of the observations:

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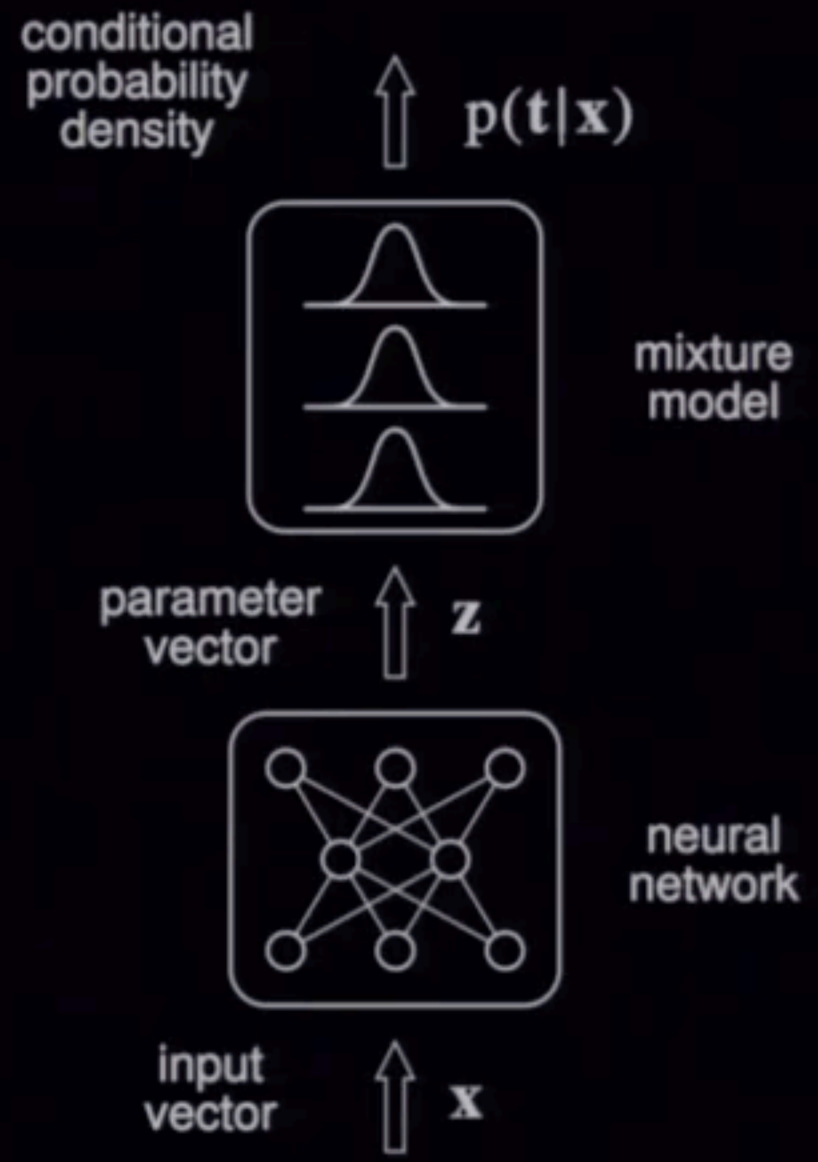
$$\boxed{q_{\phi^*}(\theta|x) \approx p(\theta|x)}$$

$\Longrightarrow$ One can asymptomatically recover the posterior by optimizing a Deep Neural Network over a simulated training set

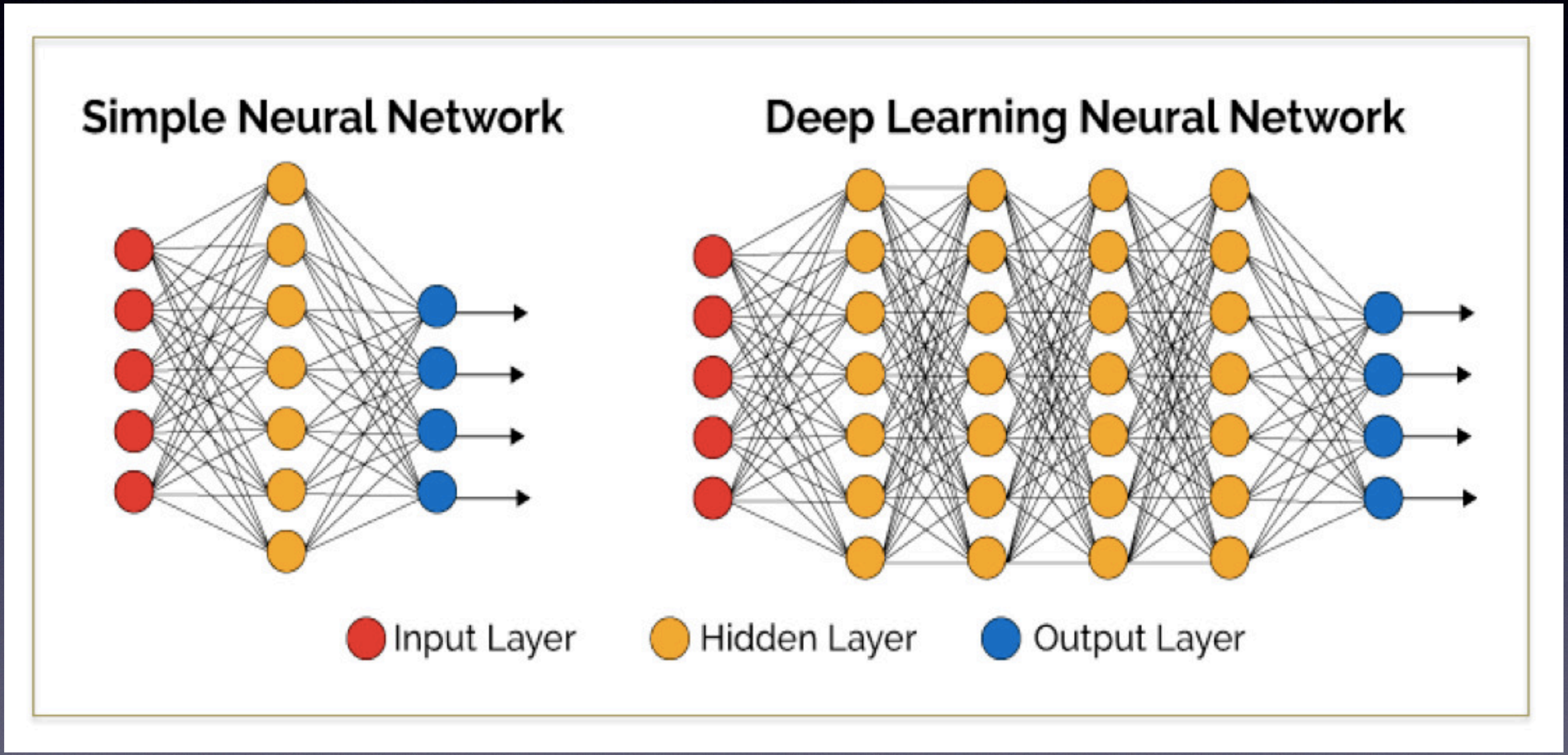
Neural Density Estimation



Bishop (1994)

A deep learning approach to cosmological dark energy

[**Escamilla-R, C.** M. Carvajal and Capozziello, S. arXiv:1910.02788
Under review (2019)]



An Artificial Neural Network (ANN) with four hidden layers and seven nodes in each hidden layer. The circles (neurons) are connected to each other through weights and biases (represented here by arrows).

A deep learning approach to cosmological dark energy

[**Escamilla-R, C.** M. Carvajal and Capozziello, S. arXiv:1910.02788
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Activation functions

$$A_{f_{\rm ELU}} = \begin{cases} \alpha(e^x - 1) & \text{for } x \leq 0, \\ x & \text{for } x > 0, \end{cases} \quad \text{in} \quad (-\alpha, \infty),$$

$$A_{f_{\rm ReLU}} = \begin{cases} 0 & \text{for } x \leq 0, \\ x & \text{for } x > 0. \end{cases} \quad \text{in} \quad [0, \infty),$$

$$A_{f_{\rm SELU}} = \begin{cases} \alpha\lambda(e^x - 1) & \text{for } x \leq 0, \\ x & \text{for } x > 0, \end{cases} \quad \text{in} \quad (-\alpha\lambda, \infty),$$

$$A_{f_{\rm Tanh}} = \tanh(c^{<t>}), \quad \text{in} \quad (-1, 1).$$

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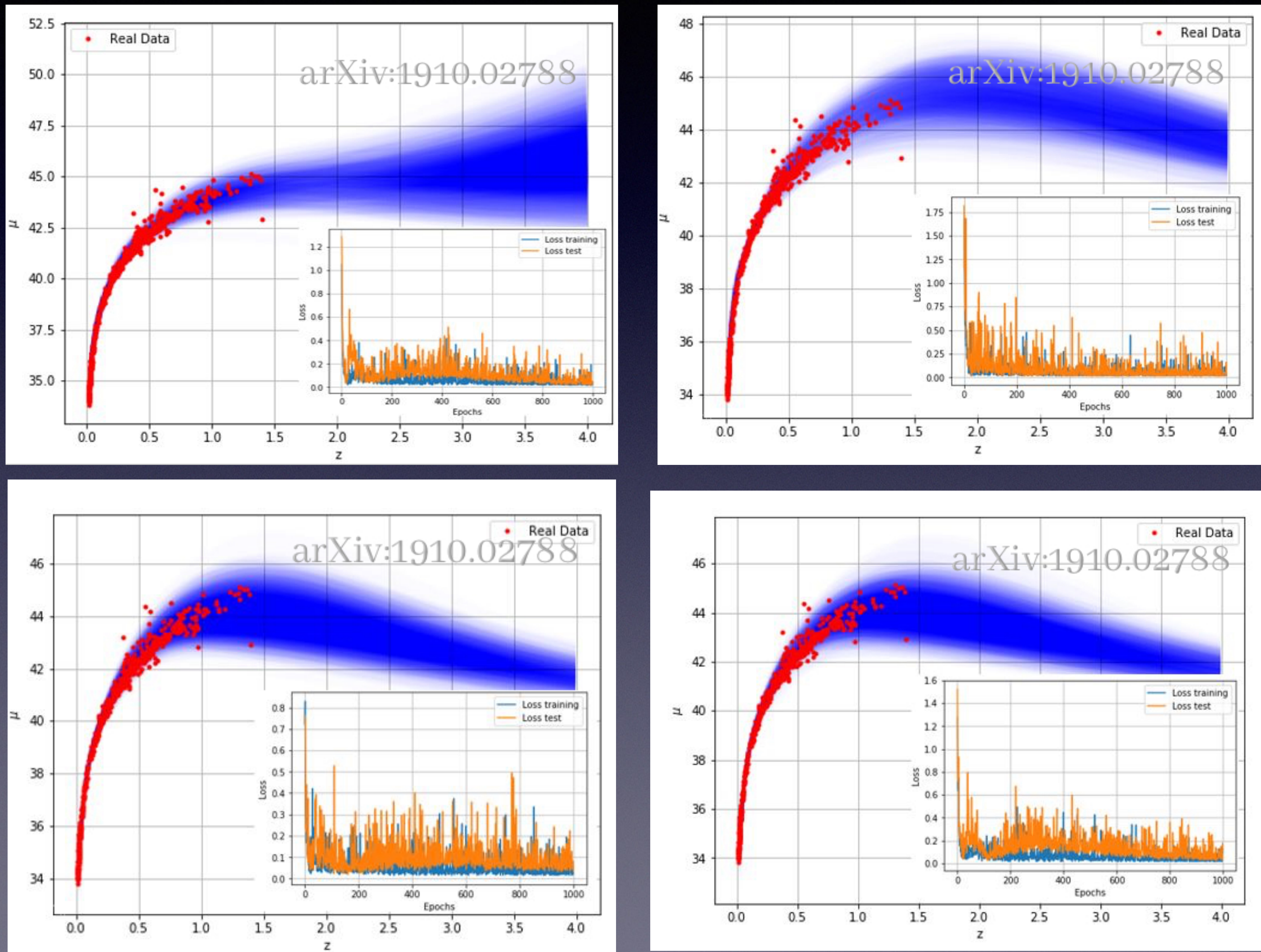

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Under review (2019)]

$$H(z)^2/H_0^2 = \Omega_m(1+z)^3 + (1-\Omega_m), \quad w_\Lambda = -1$$

$$w(z)_{\rm CPL} = w_0 + \left(\frac{z}{1+z}\right) w_1$$

$$w_{\rm gcg}(z) = -\frac{B_s}{B_s + (1-B_s)\left(\frac{1}{1+z}\right)^{-3(1+\alpha)}}$$

$$w_{\rm mcg}(z) = B - \frac{B_s(1+B)}{B_s + (1-B_s)\left(\frac{1}{1+z}\right)^{-3(1+B)(1+\alpha)}}$$

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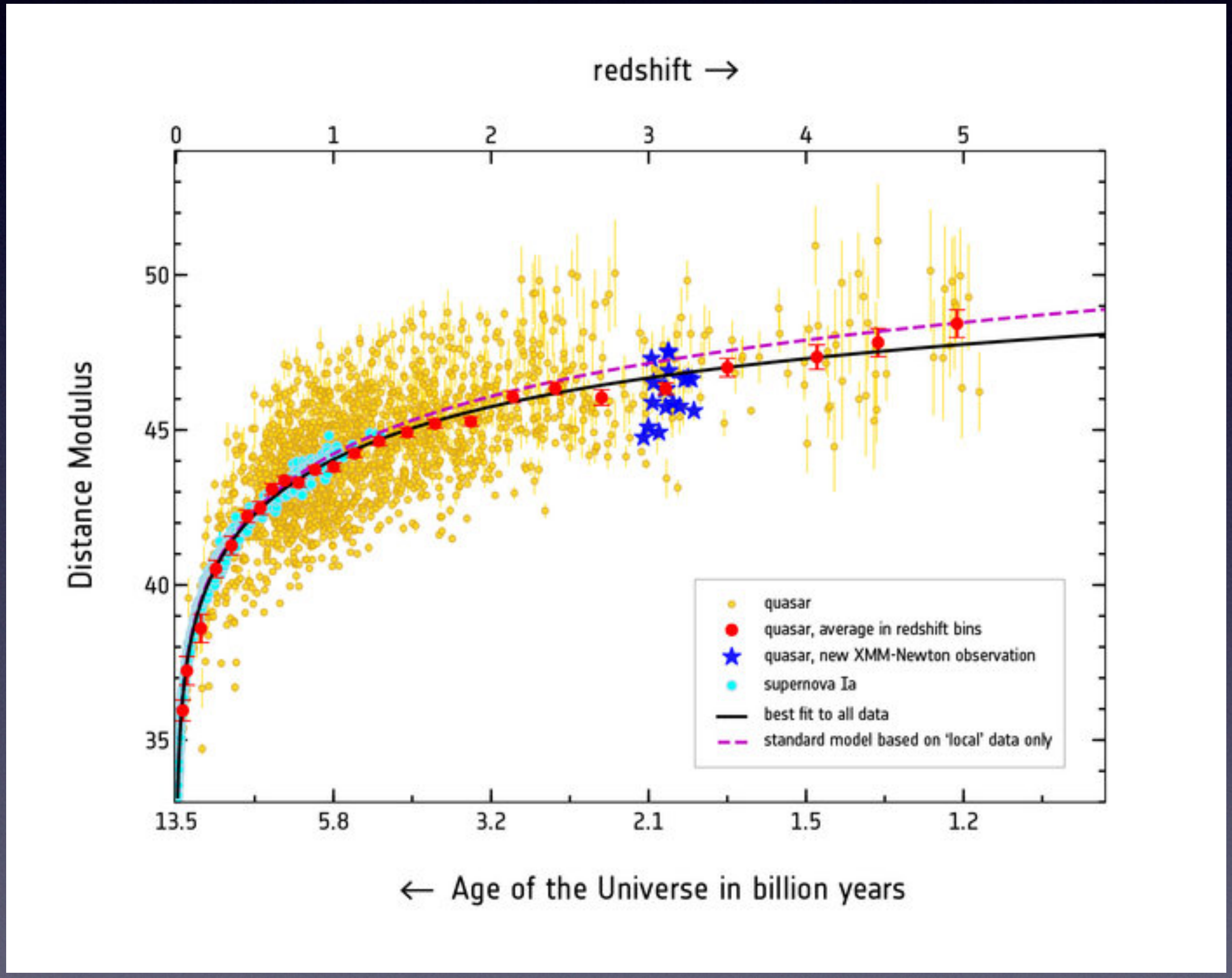

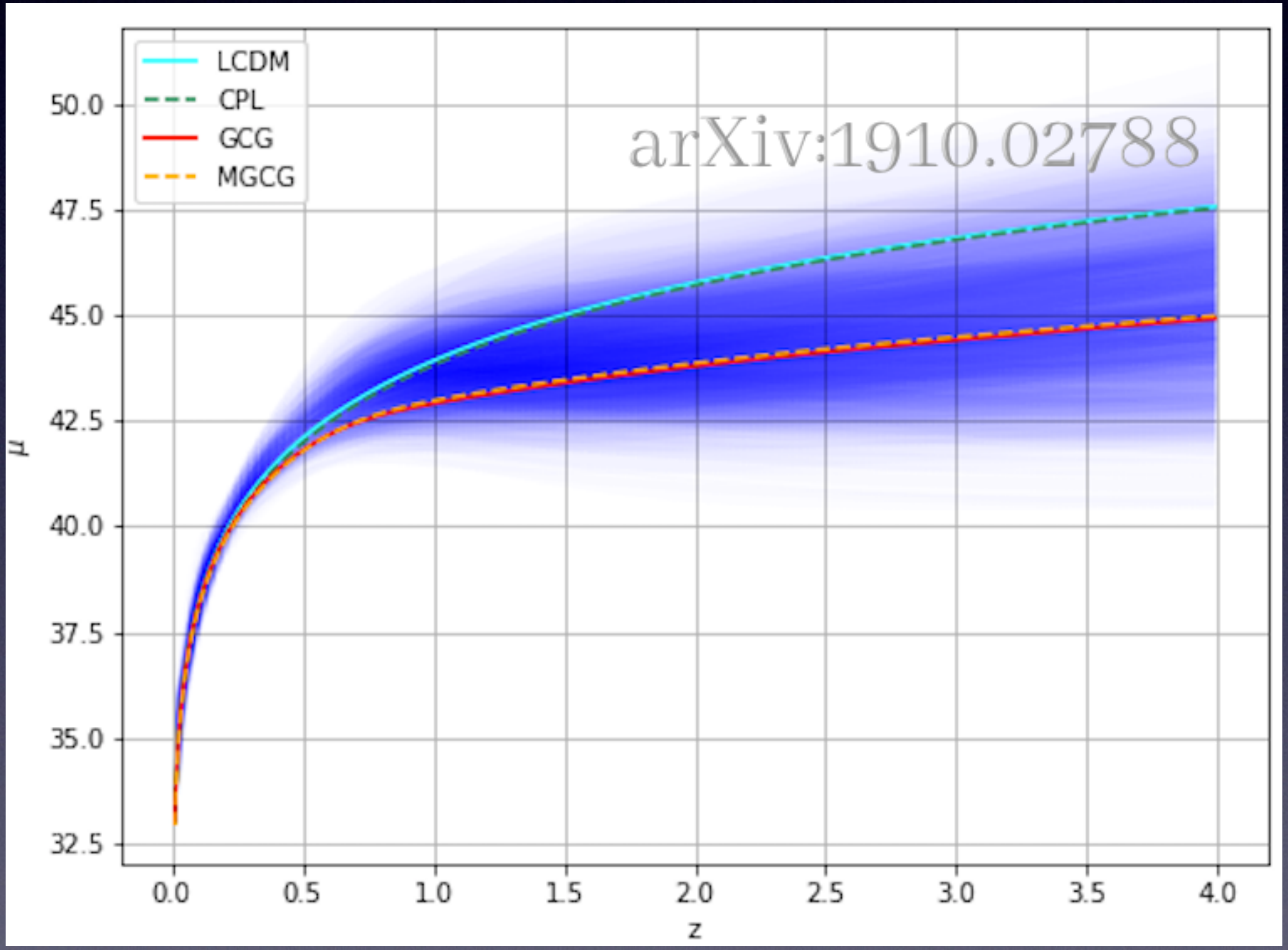

What can deep learning do for cosmology ?

- Open new and powerful ways to look at the data
  - Image detection for finding rare astrophysical objects
- New strategies for inference for increasingly complex surveys
- Data driven way of complementing our physical models
  - Modeling realistic galaxy morphologies
  - Modeling galaxy properties in numerical simulations

Thank you !